Import Libraries

In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
```

Data Loading and Initial Exploration

In [2]:
```
# Load the data
df = pd.read_csv('insurance.csv')

# Display basic information
print(f"Dataset Shape: {df.shape}")

print("\nSummary Statistics:")
display(df.describe().T)

print("\nFirst few rows:")
display(df.head())
```

```
Dataset Shape: (1338, 7)

Summary Statistics:
```

	count	mean	std	min	25%	50%	75%	max
age	1338.0	39.207025	14.049960	18.0000	27.00000	39.000	51.000000	64.00000
bmi	1338.0	30.663397	6.098187	15.9600	26.29625	30.400	34.693750	53.13000
children	1338.0	1.094918	1.205493	0.0000	0.00000	1.000	2.000000	5.00000
charges	1338.0	13270.422265	12110.011237	1121.8739	4740.28715	9382.033	16639.912515	63770.42801

```
First few rows:
```

	age	sex	bmi	children	smoker	region	charges
0	19	female	27.900	0	yes	southwest	16884.92400
1	18	male	33.770	1	no	southeast	1725.55230
2	28	male	33.000	3	no	southeast	4449.46200
3	33	male	22.705	0	no	northwest	21984.47061
4	32	male	28.880	0	no	northwest	3866.85520

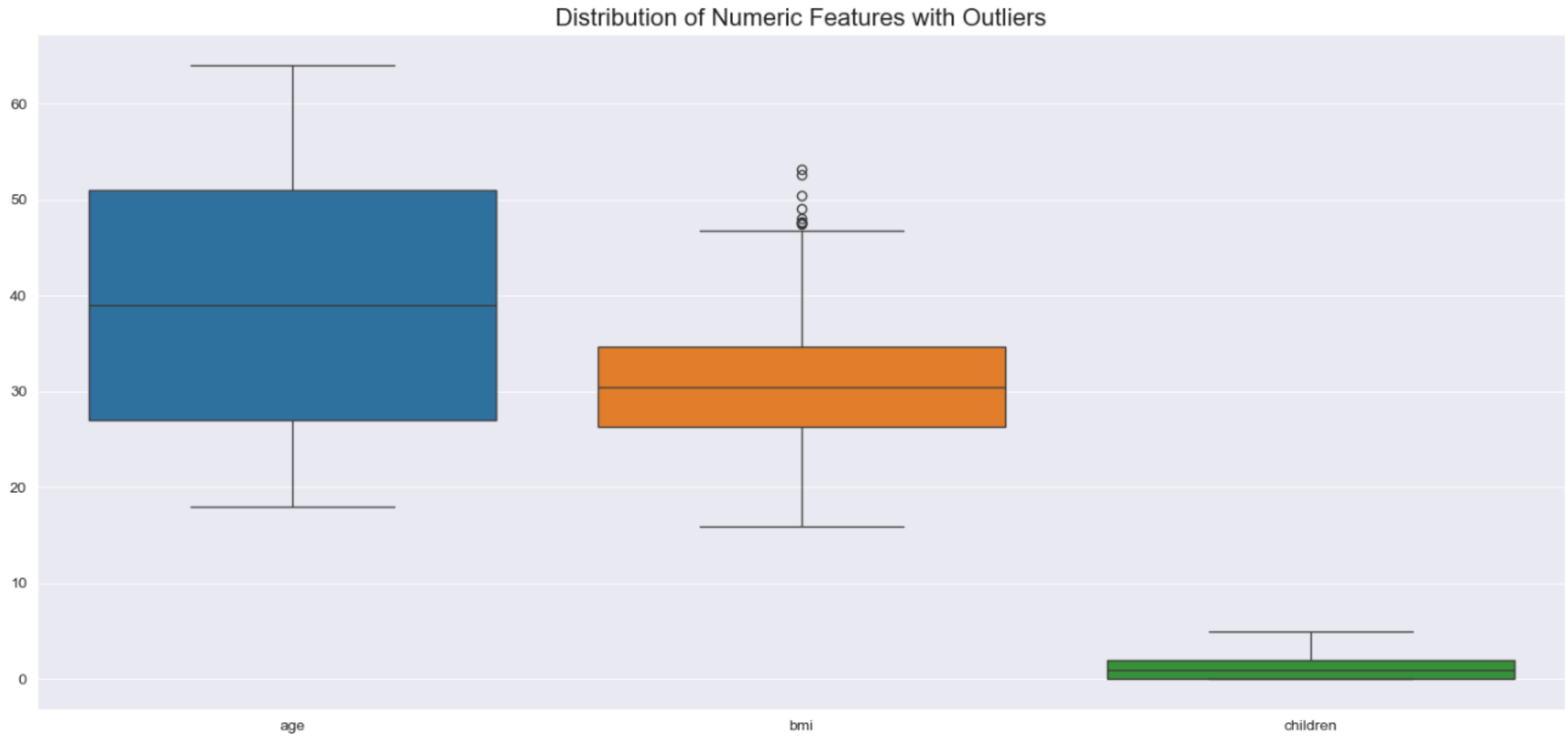
Data Cleaning and Preprocessing

In [3]:
```
# Check for missing values
print(f"Missing Values:\n{df.isna().sum()}")
# Check for duplicates
duplicates = df.duplicated().sum()
print(f"\nNumber of duplicates: {duplicates}")

# Remove duplicates if any
if duplicates > 0:
    df.drop_duplicates(inplace=True)
    print(f"New shape after removing duplicates: {df.shape}")
```

```
Missing Values:
age         0
sex         0
bmi         0
children    0
smoker      0
region      0
charges     0
dtype: int64

Number of duplicates: 1
New shape after removing duplicates: (1337, 7)
```

Outlier Detection and Handling

In [4]:
```
# Box plot for numeric features to visualize outliers
plt.figure(figsize=(18, 8))
sns.boxplot(data=df[['age', 'bmi', 'children']])
plt.title('Distribution of Numeric Features with Outliers', fontsize=16)
plt.show()

# Handle BMI outliers using IQR method
q1 = df['bmi'].quantile(0.25)
q3 = df['bmi'].quantile(0.75)
iqr = q3 - q1
lower_bound = q1 - 1.5*iqr
upper_bound = q3 + 1.5*iqr

# Filter out BMI outliers
df_clean = df[(df['bmi'] >= lower_bound) & (df['bmi'] <= upper_bound)]
print(f"Original shape: {df.shape}, After outlier removal: {df_clean.shape}")
```



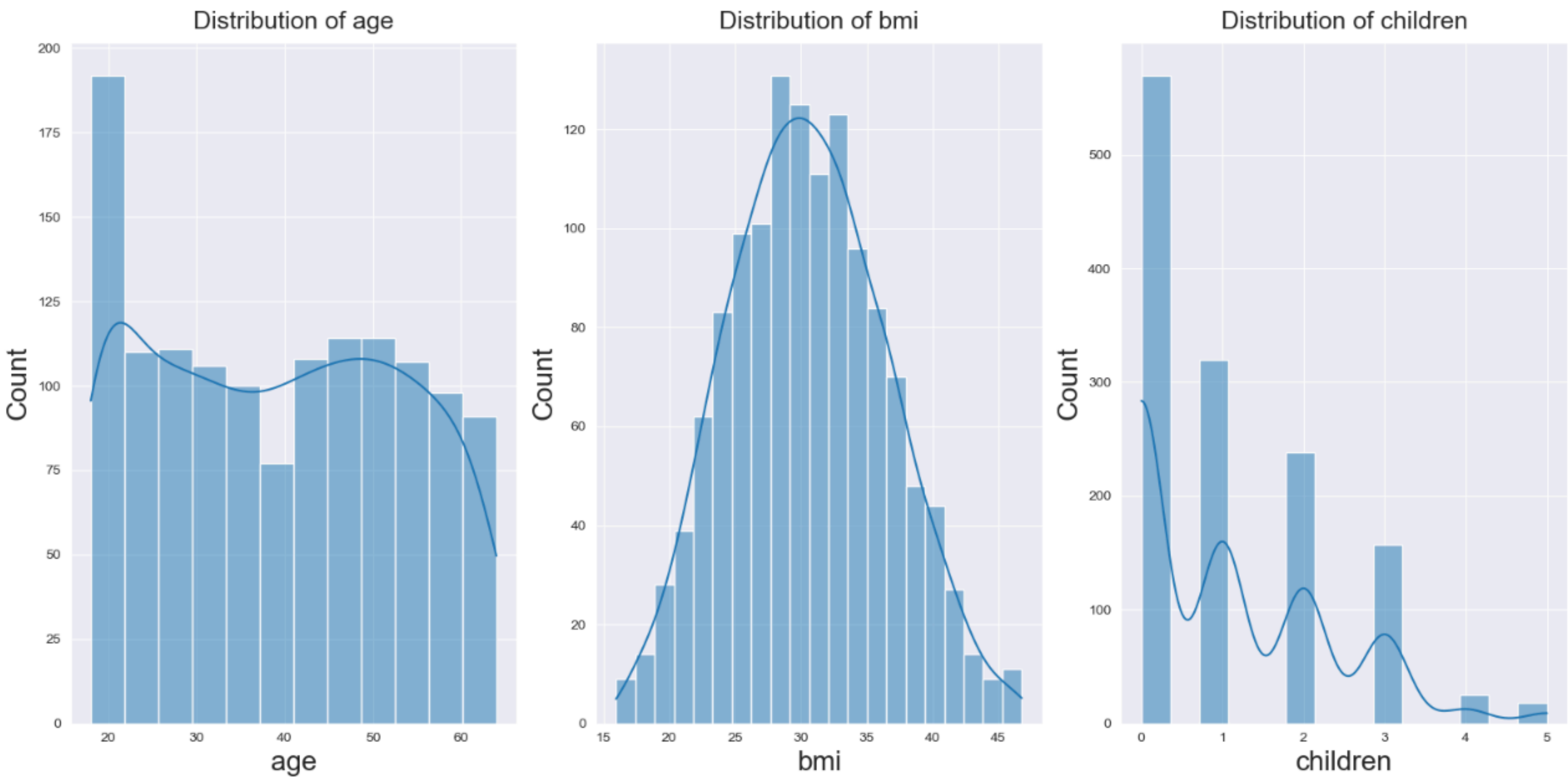

```
Original shape: (1337, 7), After outlier removal: (1328, 7)
```

Feature Engineering

In [5]:
```
# Create a copy of the cleaned dataframe
df = df_clean.copy()

# Create log transformed charges
df['log_charges'] = np.log1p(df['charges'])
```

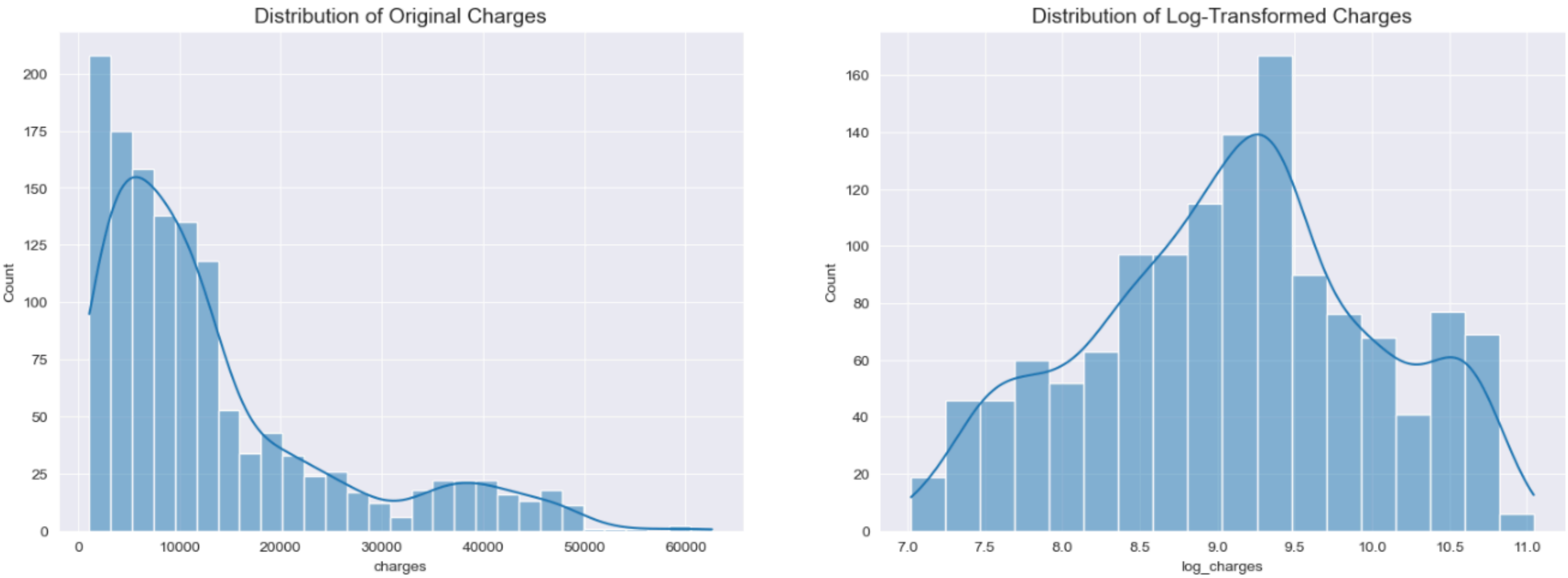
Distribution Analysis of Numeric Features

In [6]:
```
# Distribution of numeric features
num_features = df.select_dtypes(include='number')

fig, axs = plt.subplots(1, 3, figsize=(16, 8))

for i, col in enumerate(num_features.columns):
    if i < 3:  # Plot only numeric columns without charges and log_charges
        sns.histplot(df[col], kde=True, ax=axs[i])
        axs[i].set_title(f'Distribution of {col}', fontsize=18, pad=10)
        axs[i].set_xlabel(col, fontsize=20)
        axs[i].set_ylabel('Count', fontsize=20)
        axs[i].grid(True)

plt.tight_layout()
plt.show()
```



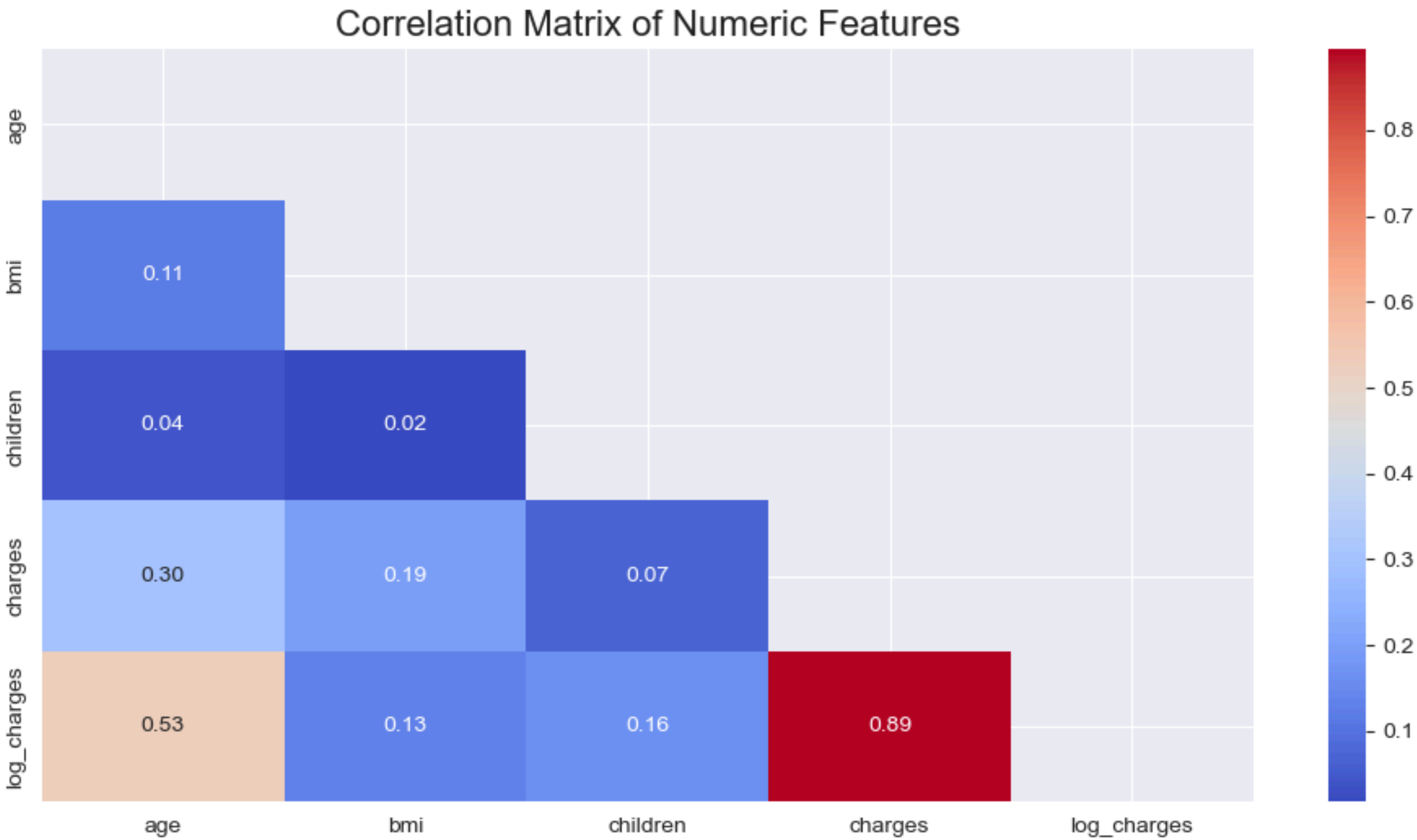
In [7]:

```python
# Compare original charges vs log-transformed charges
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(18, 6))

sns.histplot(df['charges'], kde=True, ax=ax1)
ax1.set_title('Distribution of Original Charges', fontsize=14)

sns.histplot(df['log_charges'], kde=True, ax=ax2)
ax2.set_title('Distribution of Log-Transformed Charges', fontsize=14)

plt.show()
```



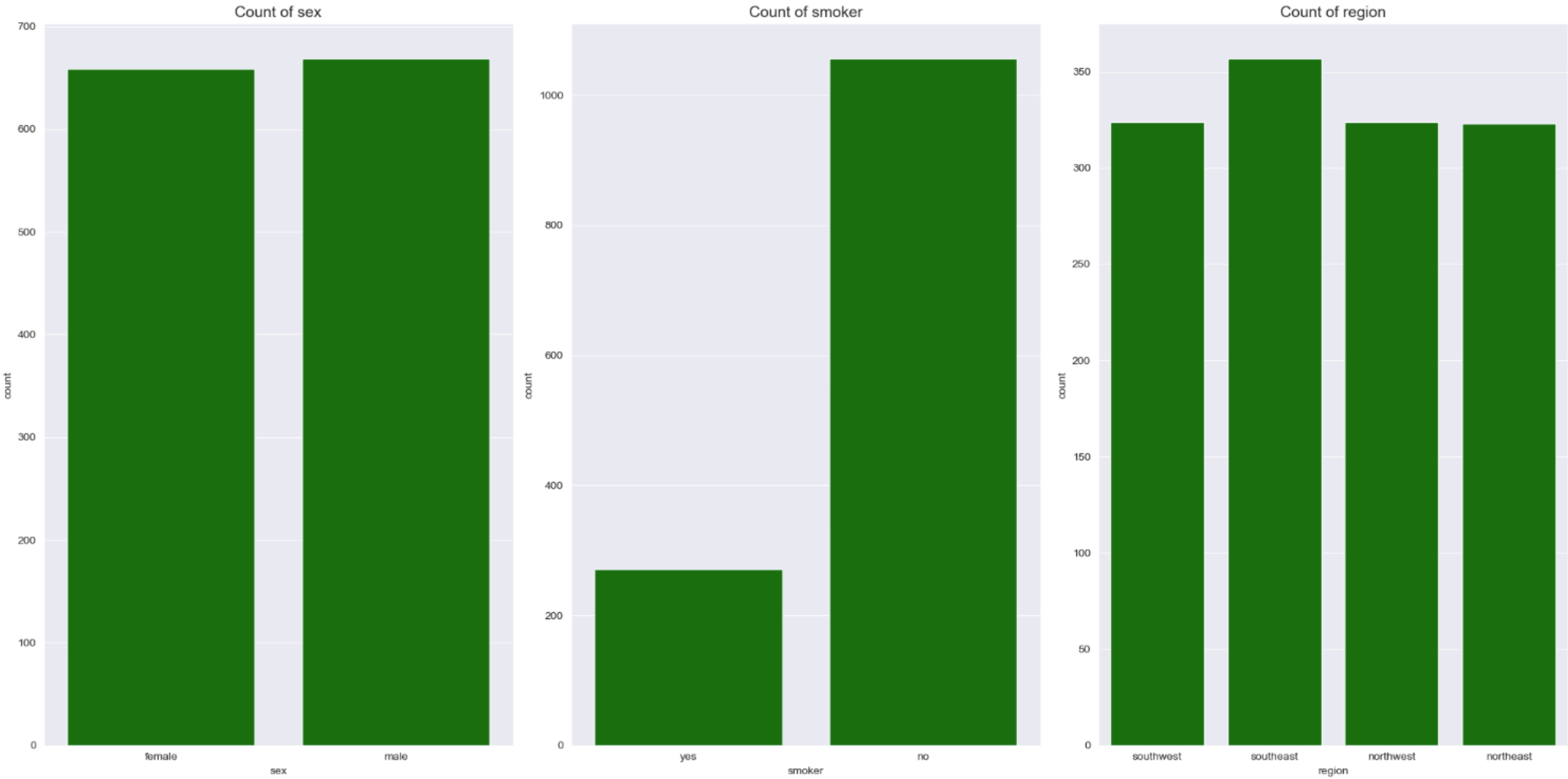
Correlation Analysis

In [8]:
```
# Correlation heatmap for numeric features
correlation = num_features.corr()
mask = np.triu(correlation)

plt.figure(figsize=(12, 6))
sns.heatmap(correlation, annot=True, fmt='.2f', cmap='coolwarm', mask=mask)
plt.title('Correlation Matrix of Numeric Features', fontsize=16)
plt.show()
```



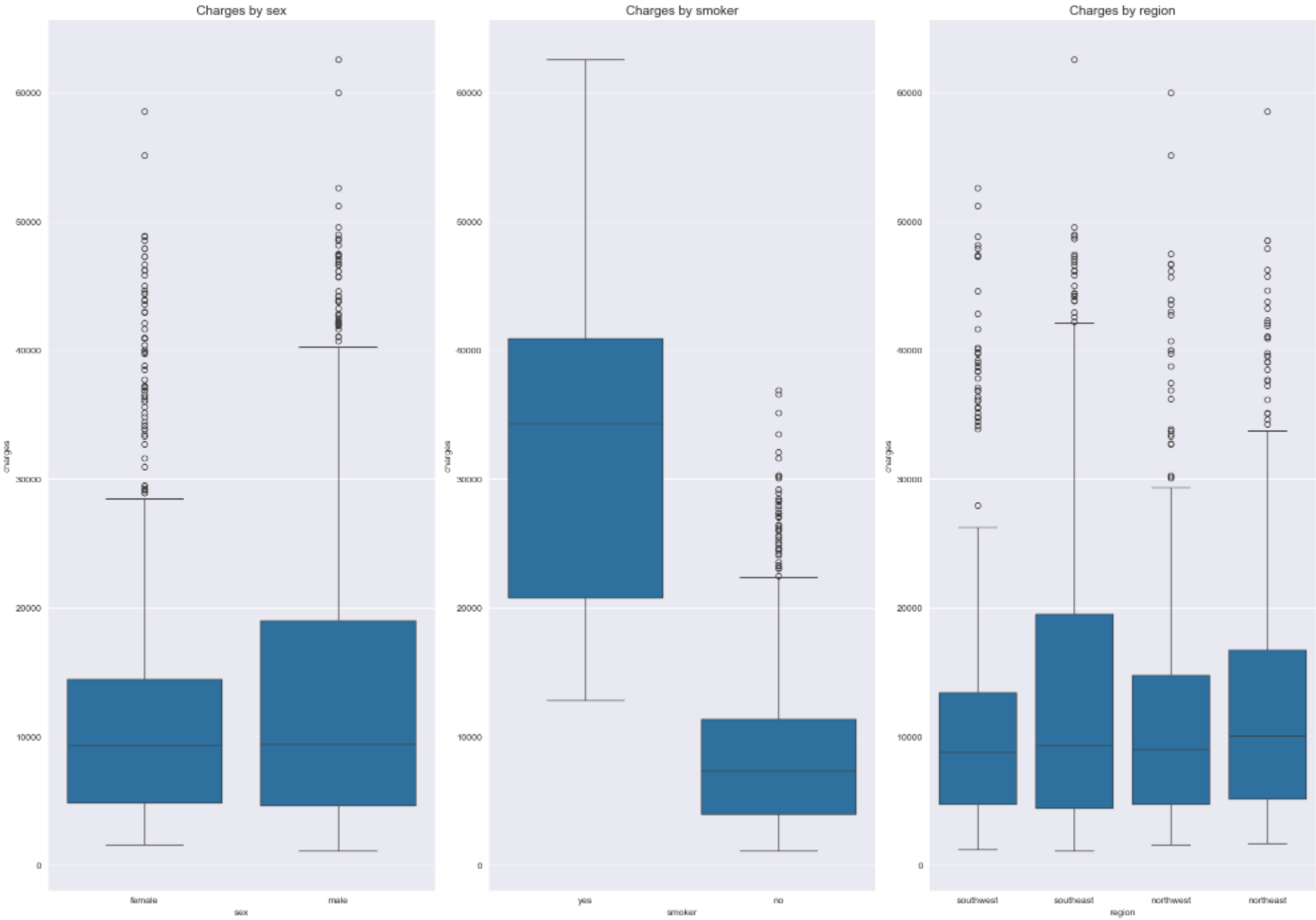
Categorical Feature Analysis

In [9]:
```python
# Define categorical features
cat_features = df.select_dtypes(include='object').columns.tolist()

# Count plots for each categorical feature
fig, axs = plt.subplots(1, 3, figsize=(20, 10))

for i, col in enumerate(cat_features):
    sns.countplot(x=col, data=df, ax=axs[i], color='green')
    axs[i].set_title(f'Count of {col}', fontsize=14)

plt.tight_layout()
plt.show()
```



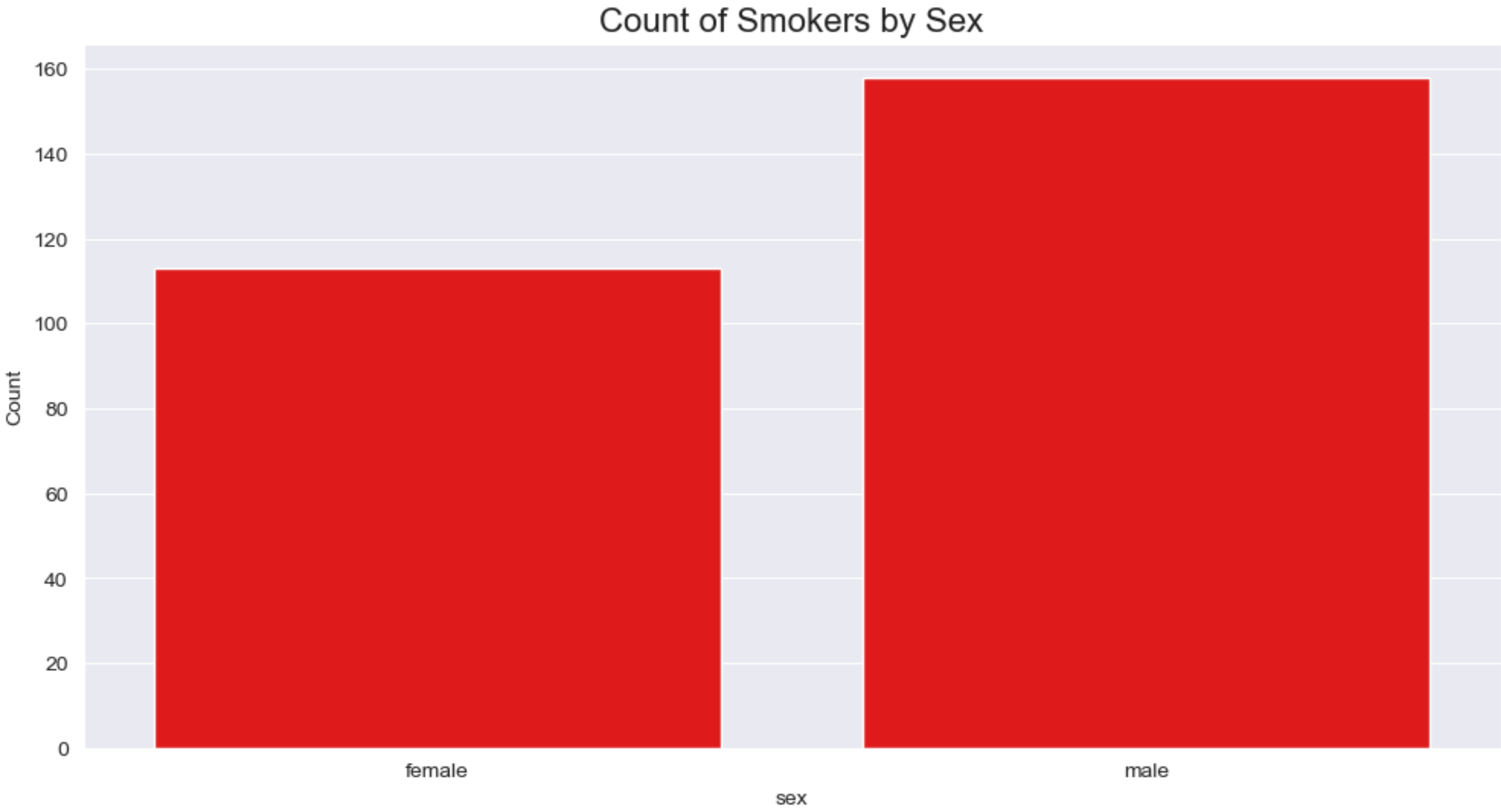
Relationship Between Categorical Features and Charges

In [10]:
```
# Box plots of charges by each categorical variable
fig, axs = plt.subplots(1, 3, figsize=(20, 14))

for i, col in enumerate(cat_features):
    sns.boxplot(x=col, y='charges', data=df, ax=axs[i])
    axs[i].set_title(f'Charges by {col}', fontsize=14)

plt.tight_layout()
plt.show()
```



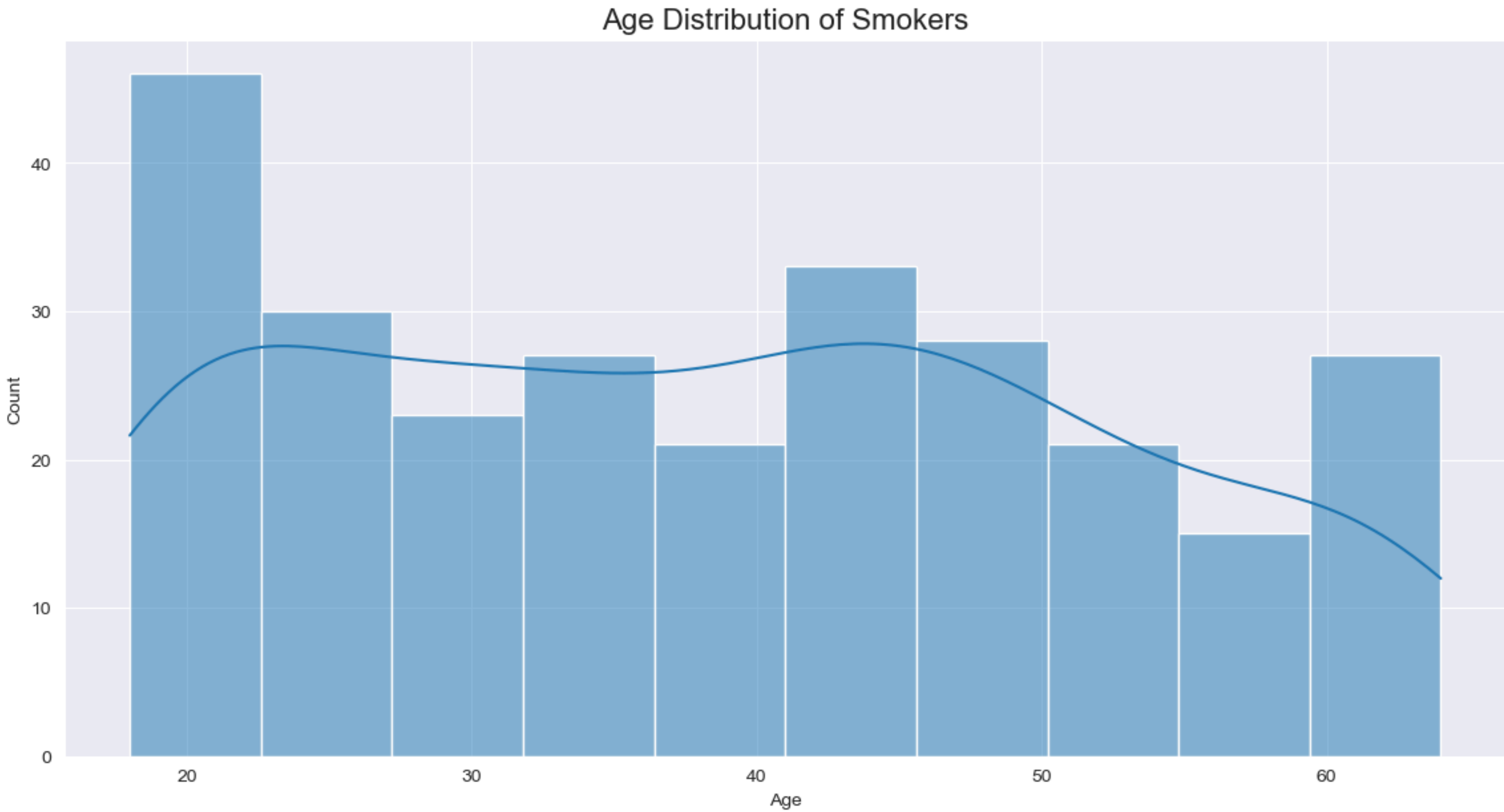
Smoker Analysis

In [11]:
```
# Create a smoker dataframe
smokers = df[df['smoker'] == 'yes']

# Count of smokers by sex
plt.figure(figsize=(12, 6))
sns.countplot(x='sex', data=smokers, color='red')
plt.title('Count of Smokers by Sex', fontsize=16)
plt.ylabel('Count')
plt.show()
```

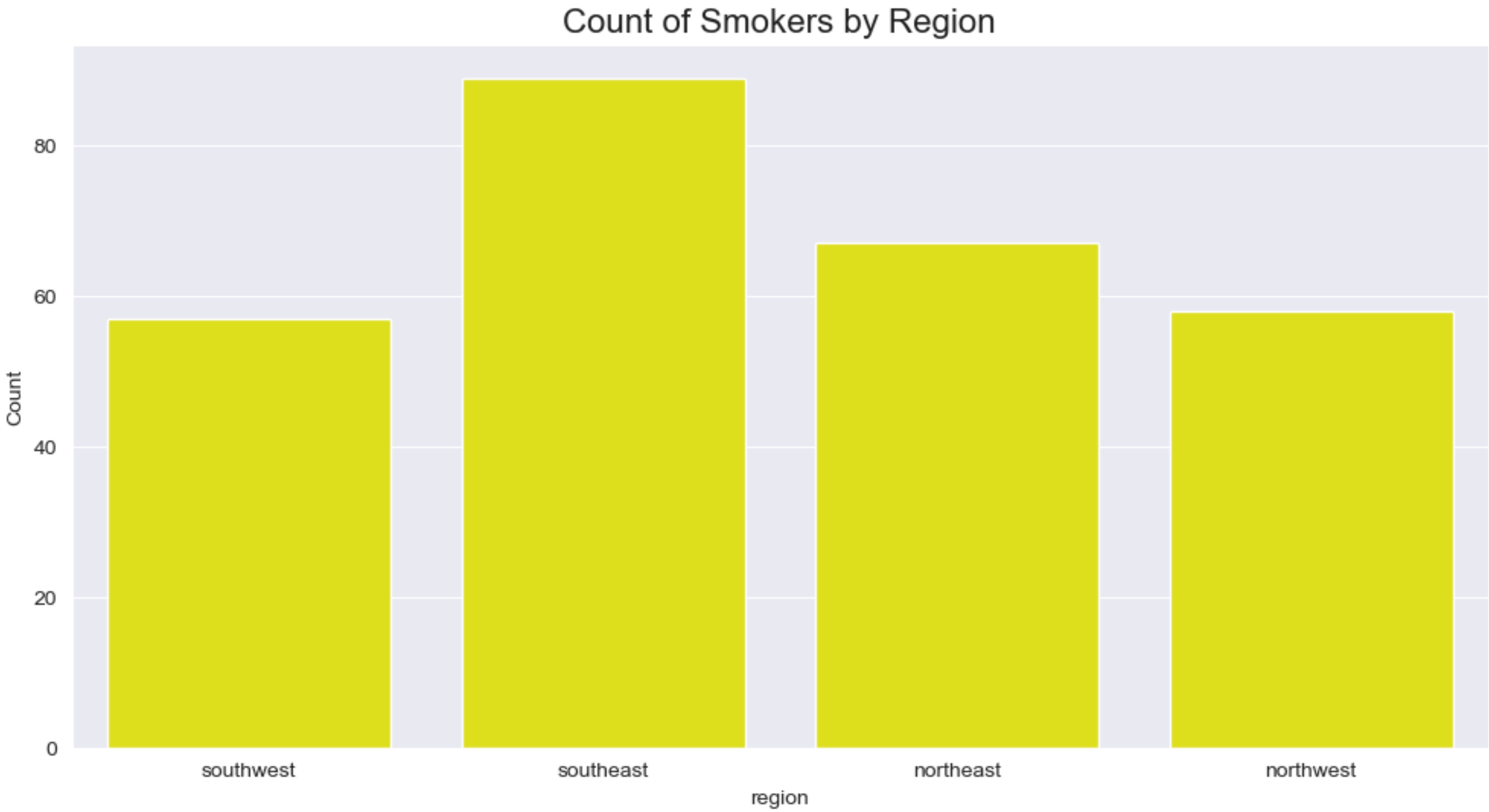


In [12]:

```
# Distribution of smokers by age
plt.figure(figsize=(14, 7))
sns.histplot(data=smokers, x='age', bins=10, kde=True)
plt.title('Age Distribution of Smokers', fontsize=16)
plt.xlabel('Age')
plt.show()
```

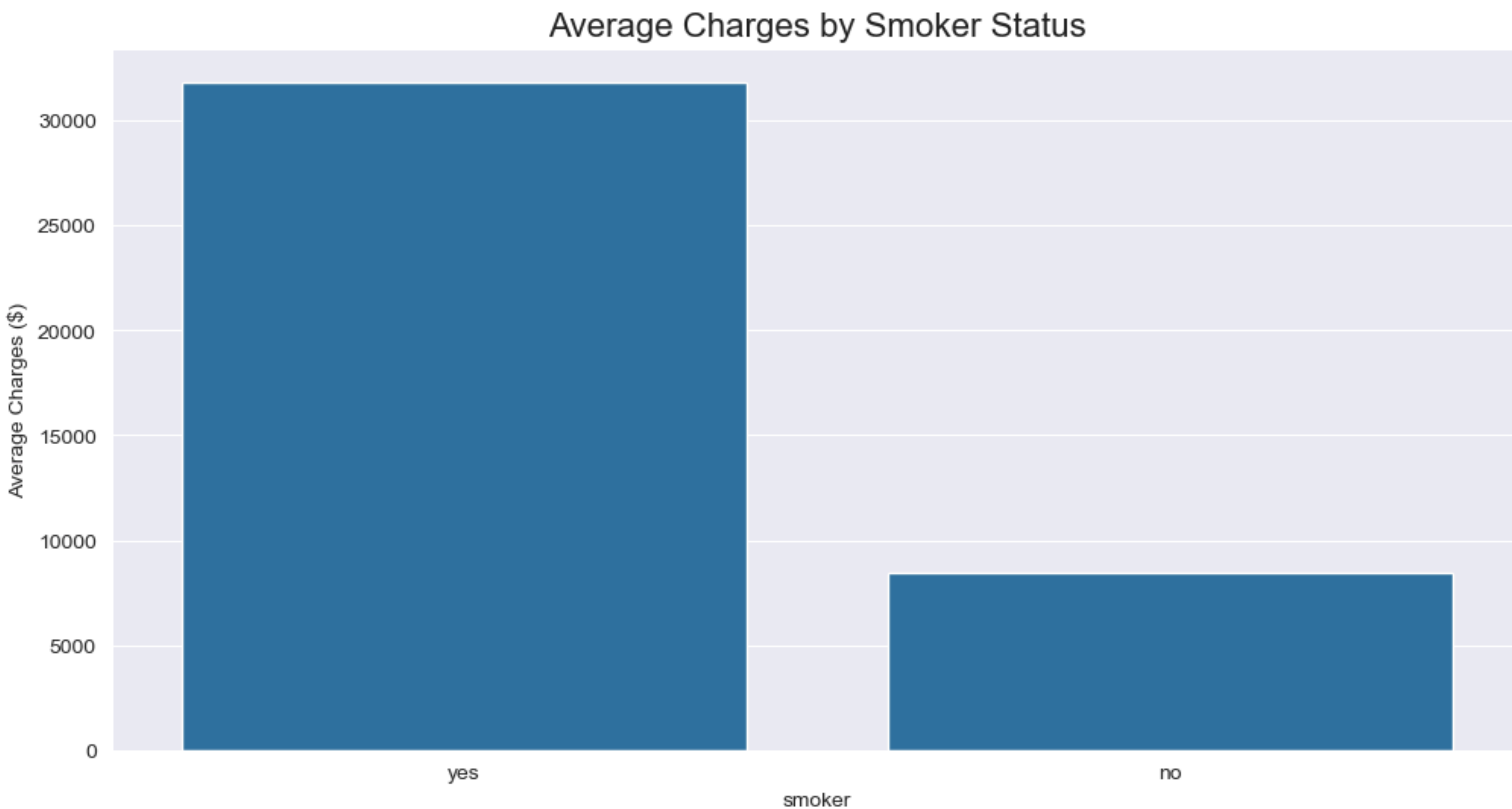


In [13]:
```
# Count of smokers by region
plt.figure(figsize=(12, 6))
sns.countplot(x='region', data=smokers, color='yellow')
plt.title('Count of Smokers by Region', fontsize=16)
plt.ylabel('Count')
plt.show()
```



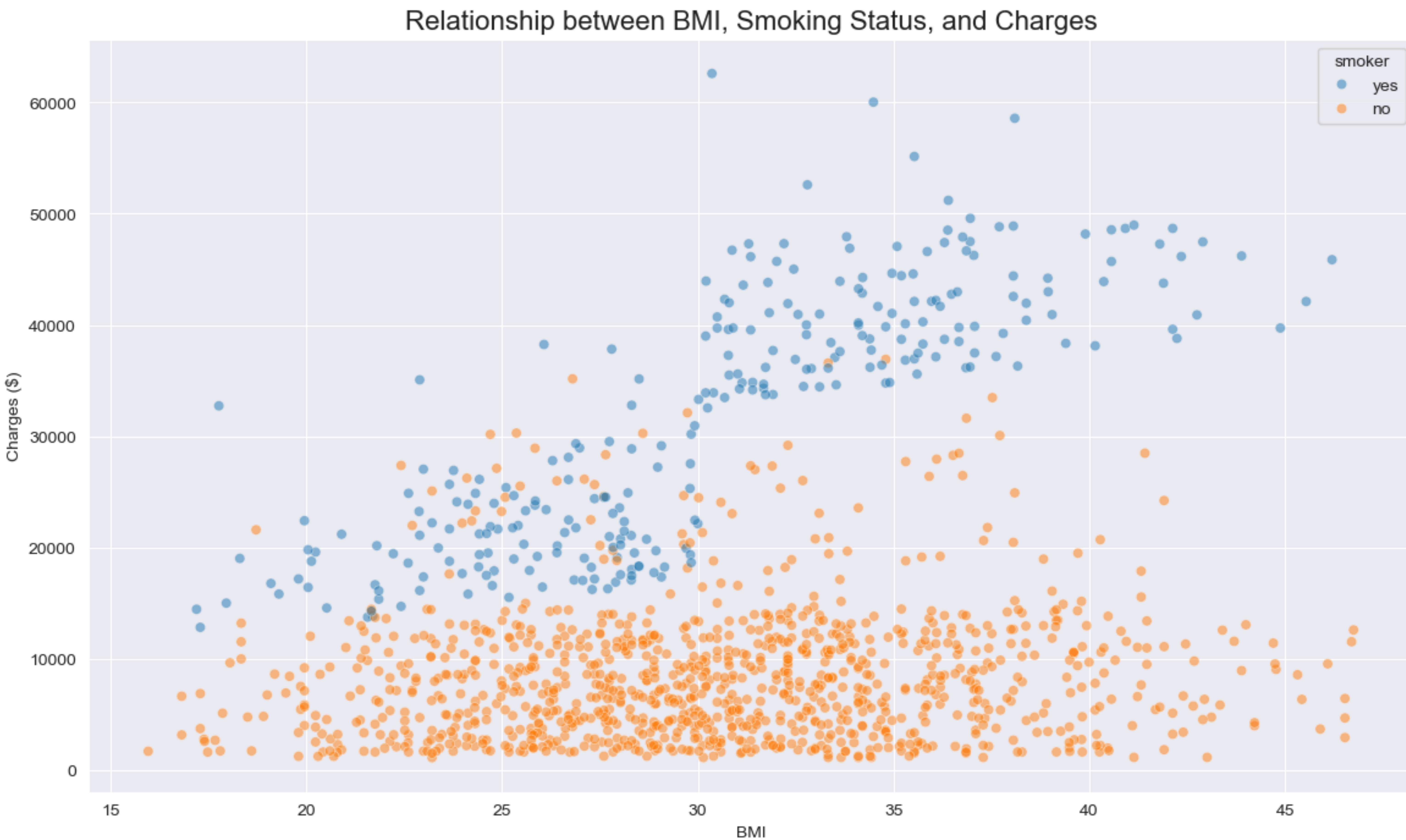
In [14]:

```
# Average charges by smoker status
plt.figure(figsize=(12, 6))
sns.barplot(x='smoker', y='charges', data=df, errorbar=None)
plt.title('Average Charges by Smoker Status', fontsize=16)
plt.ylabel('Average Charges ($)')
plt.show()
```



Multivariate Analysis

In [15]:
```
# Relationship between BMI, smoking status, and charges
plt.figure(figsize=(14, 8))
sns.scatterplot(data=df, x='bmi', y='charges', hue='smoker', alpha=0.5)
plt.title('Relationship between BMI, Smoking Status, and Charges', fontsize=16)
plt.xlabel('BMI')
plt.ylabel('Charges ($)')
plt.grid(True)
plt.show()
```



Modeling

In [16]:

```
# Prepare data for modeling by converting categorical features to
ct = ColumnTransformer(
        transformers=[
                ('onehot', OneHotEncoder(), cat_features)
    ], remainder='passthrough'
)

encoded = ct.fit_transform(df)
encoded_df = pd.DataFrame(encoded, columns=ct.get_feature_names_out())
df = encoded_df.copy()

# Define features and target
X = df.drop(['remainder__charges', 'remainder__log_charges'], axis=1)
y = df['remainder__log_charges']

# Split the data
x_train, x_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

Linear Regression Model

In [17]:
```
# Train linear regression model
model = LinearRegression()
model.fit(x_train, y_train)

# Evaluate model performance on training set
y_train_pred = model.predict(x_train)
mse_train = mean_squared_error(y_train, y_train_pred)
r2_train = r2_score(y_train, y_train_pred)

# Evaluate model performance on test set
y_test_pred = model.predict(x_test)
mse_test = mean_squared_error(y_test, y_test_pred)
r2_test = r2_score(y_test, y_test_pred)

# Print performance metrics
print("Training Set Results:")
print(f"Mean Squared Error: {mse_train:.3f}")
print(f"R² Score: {r2_train:.3f}\n")

print("Test Set Results:")
print(f"Mean Squared Error: {mse_test:.3f}")
print(f"R² Score: {r2_test:.3f}")

# Plot actual vs predicted values
plt.figure(figsize=(15, 7))
plt.scatter(y_test, y_test_pred, alpha=0.7)
plt.xlabel("Actual log(charges)")
plt.ylabel("Predicted log(charges)")
plt.title("Actual vs Predicted Insurance Charges (Log Scale)")
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()],
         color='red', label='Perfect Prediction')
plt.legend()
plt.show()
```

```
Training Set Results:
Mean Squared Error: 0.194
R² Score: 0.773

Test Set Results:
Mean Squared Error: 0.202
R² Score: 0.737
```

Conclusions:

1. Smoking status has the strongest correlation with insurance charges

2. BMI also significantly influences charges, especially for smokers

3. Age shows a positive correlation with insurance costs

4. There are regional differences in insurance pricing